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DG Allocation and Sizing in Distribution Network Using Modified Shuffled Frog Leaping Algorithm

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Abstract-- Distributed generation (DG) will have a growing role in the future of the power systems. DG reduces line losses and improves system voltage profile. Many researchers have used evolutionary methods for finding the optimal DG placement. The present study indicates that placing and application of DGs by modified shuffled frog leaping algorithm (MSFLA) will reduce losses and improve voltage profile of power systems. Voltage Profile Improvement Index (VPII) and Line Loss Reduction Index (LLRI) are analyzed in the paper. The MSFLA is simulated with MATLAB software on IEEE-70 bus radial distribution system. Test results indicate that MSFLA method can obtain better results than the SFLA method on the 70-bus radial distribution systems.

Keyword: Distributed Generation (DG); Line Loss Reduction Index; Modified Shuffled Frog Leaping Algorithm (MSFLA); Voltage Profile.

1. INTRODUCTION

A distributed power unit can be connected directly to the consumer or to a utility's transmission or distribution system to provide peaking services .Distributed generation provides a multitude of services to utilities and consumers, including standby generation, peaks chopping capability, base load generation.

The key element of this new environment is to build and operate several DG units near load centers instead of expanding the central-station power plants located far away from customers to meet increasing load demand. Distributed generation technologies can enhance the efficiency, reliability, voltage profile, and operational benefits of the distribution system. DG can be powered by both conventional and renewable energy sources [1]. Several DG options are fast becoming economically viable [2-3]. Technologies that utilize conventional energy sources includes gas turbines, micro turbines and else engines. Currently, the ones that show promises for DG applications are wind electric conversion systems, geothermal systems, solar-thermal–electric systems, photovoltaic systems and fuel cells [4-5].

A stochastic dynamic multi-objective model for integration of DG in distribution networks is proposed in [6] with a binary PSO algorithm. A distribution system expansion planning strategy encompassing renewable DG systems with schedulable and intermittent power generation patterns is presented in [7] that a solution algorithm integrating TRIBE PSO and ordinal optimization (OO) is developed to obtain optimal and near-optimal solutions for system planners. A DG interconnection planning study framework is brought in [8] that includes a coordinated feeder reconfiguration and voltage control to calculate the maximum allowable DG capacity at a given node in the distribution network. In [9] a distributed micro-grid planning model has been presented to optimize the locating and the unit capacities within DG micro-grid, in which wind power and photovoltaic power are taken into consideration simultaneously with both Elitism Genetic Algorithm (EGA) and PSO.

A multi-objective index-based approach for optimally determining the size and location of multi-distributed generation (multi-DG) units in distribution systems with different load models based on PSO is introduced in [10,11] and a combined genetic algorithm (GA)/(PSO) is presented in [12] for optimal location and sizing of DG on distribution systems. A population-based heuristic approach for optimal location and capacity of DGs in distribution networks, with the objectives of minimization of fuel cost, power loss reduction, and voltage profile improvement is proposed in [13] that the approach employs an improved group search optimizer (iGSO) by incorporating PSO into group search optimizer (GSO) for optimal setting of DGs. A new hybrid method which employs discrete PSO and optimal power flow is introduced in [14] which could apply to connect distributed generation systems in a distribution network choosing among a large number of potential combinations.

This paper presents a modified shuffled frog leaping algorithm (MSFLA) for Distributed Generation Allocation and sizing to Reduce Losses and Improve Voltage Profile processes. The SFLA is a meta-heuristic search method inspired from the memetic evolution of a group of frogs when seeking for food. It consists of a frog leaping rule for local search and a memetic shuffling rule for global information exchange. In this paper, a new frog leaping rule is proposed to

improve the local exploration of the SFLA. The main idea behind the new frog leaping rule is to extend the direction and the length of each frog's jump by emulating frog's perception and action uncertainties. The modification widens the local search space, thus helps to prevent premature convergence and improves the performance of the SFLA. The proposed method is easy to implement and program with basic mathematical and logic operations. It can also handle objective functions with stochastic nature and does not require a good initial solution to start its iteration process.

2. APPROACH TO QUANTIFY THE BENEFITS OF DG

In order to evaluate and quantify the benefits of distributed generation suitable mathematical models must be employed along with distribution system models and power flow calculations to arrive at indices of benefits. Among the many benefits two major ones are considered: Voltage profile improvement, line loss reduction.

2.1 Line Loss Reduction Index

Another major benefit offered by installation of DG is the reduction in electrical line losses [15]**.** By installing DG line currents can be reduced, thus helping to reduce electrical line losses. The proposed line loss reduction index (LLRI) is defined as

$$LLRI = \frac{LL_{W/DG}}{LL_{WO/DG}} \tag{1}$$

Where, LLw/DG is the total line losses in the system with the employment of DG and LLwo/DG is the total line losses in the system without DG and it can be

$$LL_{W/DG} = 3\sum_{i=1}^{M} I_i^{\,2} \times R \times D_i \tag{2}$$

Where, I_i is the per unit line current in distribution line i with the employment of DG, R is the line resistance (pu/km), D_i is the distribution line length (km), and M is the number of lines in the system.

Similarly, LLwo/DG is expressed as

$$LL_{Wo/DG} = 3\sum_{i=1}^{M} I_i^{\,2} \times R \times D_i \tag{3}$$

where, I_i is the per-unit line current in distribution line i without DG.

Based on this definition, the following attributes are:

LLRI <1, DG has reduced electrical line losses,

LLRI =1, DG has no impact on system line losses,

LLRI >1, DG has caused more electrical line losses.

This index can be used to identify the best location and sizing to install DG to maximize the line loss reduction.

2.2 Voltage Profile Improvement Index

The inclusion of DG results in improved voltage profile at various buses. The Voltage Profile Improvement Index (VPII) quantifies the improvement in the voltage profile (VP) with the inclusion of DG [15]. It is expressed as,

$$VPII = \frac{VP_{W/DG}}{VP_{WO/DG}} \tag{4}$$

Based on this definition, the following attributes are:

VPII < 1, DG has improved the voltage profile of the system,

VPII = 1, DG has no impact on the system voltage profile,

VPII > 1 DG has not beneficial.

Where, VP $_{W/DG}$, VP $_{Wo/DG}$ are the measures of the voltage profile of the system with DG and without DG respectively. The general expression for VP is given as,

$$VP = \sum_{i=1}^{N_{bus}} \left| V_i - V_{i,ref} \right| \tag{5}$$

where, V_i is the Magnitude of voltage of bus i. $V_{i,ref}$ is the Magnitude of voltage of bus slack for VP provides an opportunity to quantify and aggregate the importance, amounts, and the voltage levels at which loads are being supplied at the various load busses in the system. This expression should be used only after making sure that the voltages at all the load busses are within allowable minimum and maximum limits, typically between 0.95 p.u. and 1.05p.u. In this case all the load buses are given equal importance. In reality, DG can be installed almost anywhere in the system. Therefore, VPII can be used to select the best location for DG.

3. LOAD FLOW

On account of the some inherent features of distribution systems such as; radial structure, unbalanced distributed loads, large number of nodes, a wide range of R/X ratios; the conventional techniques developed for transmission systems generally fail on the determination of optimum size and location of distributed generations. In this study, the proposed methodology is based on the equivalent current injection that uses the Bus–Injection to Branch-Current (BIBC) and Branch-Current to Bus-Voltage (BCBV) matrices which were developed based on the topological structure of the distribution systems and is implemented for the load flow analysis of the distribution systems. The details of both matrices can be found in [16].The methodology proposed here requires only one base case load flow to determine the optimum size and location of DG. Detailed description of BIBC and BCBV matrix's building algorithm is omitted due to the lack of space and can be found in [16].

4. THE PROPOSED MSFLA OPTIMIZATION OF DG LOCATION AND CAPACITY IN A RADIAL DISTRIBUTION SYSTEM

4.1 The Objective Function

The proposed work aims at minimizing the combined objective function designed to reduce power loss and also improve voltage profile system for various values of distributed generations. The main objective function is defined as

$$\min F_{total} = P_{loss} + \sum_{p=1}^{n} \lambda_p \left(V_p\right)^2 \tag{6}$$

where, λ_p is the penalty factor of bus voltages and is heuristically taken as 1,P_{loss} is the real power loss obtained from the load flow solution at the base case, V_P is the voltage profile of the buses.

4.2. Constraints

The constraints are listed as follows:

• Distribution line absolute power limits

$$\left|P_{ij}^{Line}\right| \le p_{ij.\max}^{Line} \tag{7}$$

$\left|P_{ij}^{Line}\right|$ and $p_{ij,\max}^{Line}$ are the absolute power and its corresponding maximum allowable value flowing over the distribution line between the nodes i and j, respectively.

• Bus voltage limit Bus voltage amplitudes are limited as

$$V_{min} \le V_i \le V_{max} \tag{8}$$

Where V_{min} and V_{max} are the minimum and maximum values of bus voltage amplitudes, respectively.

• Radial structure of the network

$$M = N_{bus} - N_f \tag{9}$$

Where M is the number of branches, N_{bus} is the number of nodes and N_f is the number of sources.

• Power limits of DG

$$Q_{DGi}^{\min} \le Q_{DGi} \le Q_{DGi}^{\max}$$

and

$$P_{DGi}^{\min} \le P_{DGi} \le P_{DGi}^{\max} \tag{10}$$

Where P_i and Q_i are the injected active and reactive power of DG components at the ith bus.

• Subject to power balance constraints

$$\sum_{i=1}^{N_{sc}} P_{DGi} = \sum_{i=1}^{N_{SC}} P_{Di} + P_L \tag{11}$$

Where: N_{sc} is total number of sections, P_L is the real power loss in the system, P_{DGi} is the real power generation DG at bus i, P_{Di} is the power demand at bus i.

4.3 Modified Shuffled Frog Leaping Algorithm

4.3.1 Shuffled frog-leaping algorithm

The SFLA is a meta-heuristic optimization method that mimics the memetic evolution of a group of frogs when seeking for the location that has the maximum amount of available food. The algorithm contains elements of local search and global information exchange ([17], [18]). The SFLA involves a population of possible solutions defined by a set of virtual frogs that is partitioned into subsets referred to as memeplexes. Within each memeplex, the individual frog holds ideas that can be influenced by the ideas of other frogs, and the ideas can evolve through a process of memetic evolution.

The SFLA performs simultaneously an independent local search in each memeplex using a particle swarm optimization like method.To ensure global exploration, after a defined number of memeplex evolution steps (i.e. local search iterations), the virtual frogs are shuffled and reorganized into new memeplexes in a technique similar to that used in the shuffled complex evolution algorithm. In addition, to provide the opportunity for random generation of improved information, random virtual frogs are generated and substituted in the population if the local search cannot find better solutions. The local searches and the shuffling processes continue until defined convergence criteria are satisfied. The flowchart of the SFLA is illustrated in Fig.1.

The local search block in the flowchart is shown later in Fig. 5. The SFLA is described in details as follows. First, an initial population of N frogs $P = \{X_1, X_2, ..., X_N\}$ is created randomly. For S-dimensional problems (S variables), the position of a frog i^{th} in the search space is represented as $X_i = [x_1, x_2, \ldots, x_{iS}]^T$.A fitness function is defined to evaluate the frog's position. For minimization problems, the frog's fitness can be defined as,

$$fitness = 1/[\, f(X) + C] , \tag{12}$$

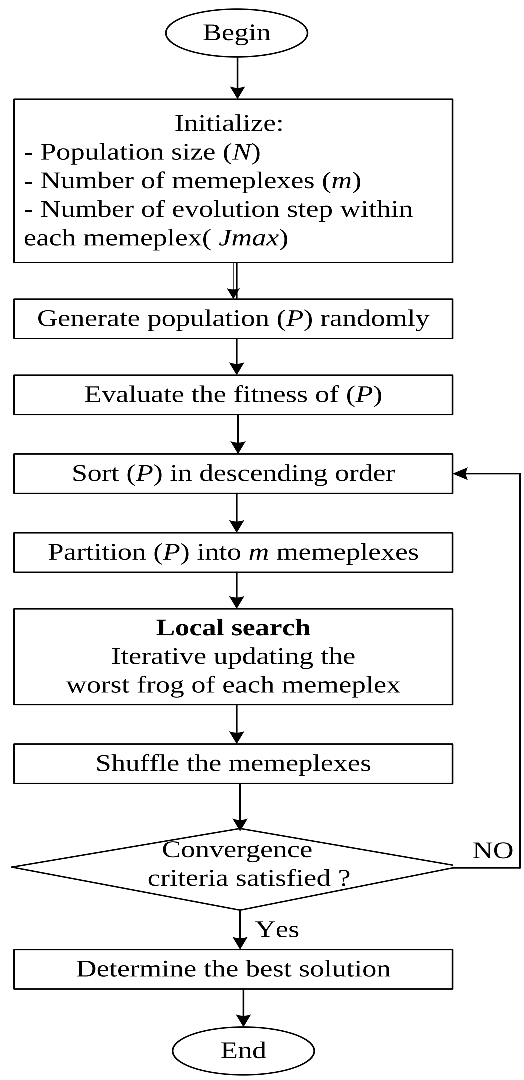

Figure 1: Flowchart of the SFLA

and for maximization problem, the frog's fitness can be simply defined as,

$$\text{fitness} = f(X) + C, \quad (13)$$

Where f(X) is the cost function to be optimized, and *C* is a constant chosen to ensure that the fitness value is positive. Afterwards, the frogs are sorted in a descending order according to their fitness. Then, the entire population is divided into m memeplexes, each containing n frogs (i.e.$N = m \times n$), in such a way that the first frog goes to the first memeplex, the second frog goes to the second memeplex, the m^{th} frog goes to the m^{th} memeplex, and the $(m+1)^{th}$ frog goes back to the first memeplex, etc.Fig. 2 illustrate this memeplex partitioning process.

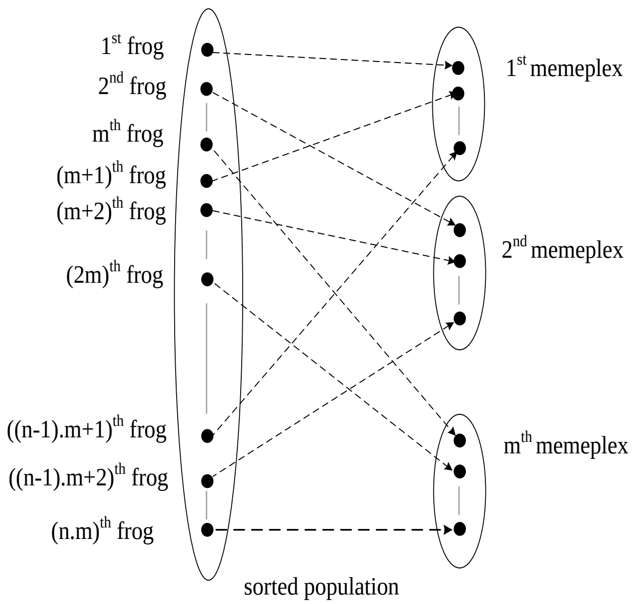

Figure.2: Memeplex partitioning process

Let M_k is the set of frogs in the k^{th} memeplex, this dividing process can be described by the following expression:

$$M_k = \{X_{K+m(l-1)} \in P | 1 \leq l \leq n\}, (1 \leq k \leq m) \quad (14)$$

Within each memeplex, the frogs with the best and the worst fitness are identified as X_b and X_w, respectively. Also, the frog with the global best fitness is identified as X_g. During memeplex evolution, the worst frog X_w leaps toward the best frog X_b. According to the original frog leaping rule, the position of the worst frog is updated as follows:

$$D = r.(X_b - X_w), \quad (15)$$

$$X_w(\text{new}) = X_w + D, (|D| < D_{max}), \quad (16)$$

Where r is a random number between 0 and 1; and D_{max} is the maximum allowed change of frog's position in one jump. Fig. 3 demonstrates the original frog leaping rule. If this leaping produces a better solution, it replaces the worst frog. Otherwise, the calculations in (15) and (16) are repeated but respect to the global best frog (i.e. X_g replaces X_b). If no improvement becomes possible in this case, the worst frog is deleted and a new frog is randomly generated to replace it.

The calculations continue for a predefined number of memetic evolutionary steps within each memeplex, and then the whole population is mixed together in the shuffling process. The local evolution and global shuffling continue until convergence criteria are satisfied. Usually, the convergence criteria can be defined as follows:

i. The relative change in the fitness of the best frog within a number of consecutive shuffling iterations is less than a pre-specified tolerance;

ii. The maximum user-specified number shuffling iterations is reached.

The SFLA will stop when one of the above criteria is arrived first.

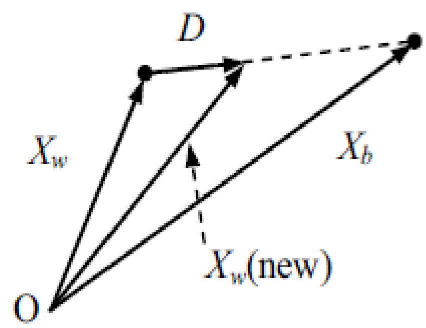

Figure. 3. The original frog leaping rule

4.3.2 Modification of the frog leaping rule

In the natural memetic evolution of a frog population, the ideas of the worse frogs are influenced by the ideas of the better frogs, and the worse frogs tend to jump toward the better ones for the possibility of having more foods. The frog leaping rule in the SFLA is inspired from this social imitation, but it performs only the jump of the worst frog toward the best one. According to the original frog leaping rule presented above, the possible new position of the worst frog is restricted in the line segment between its current position and the best frog's position, and the worst frog will never jump over the best one (see Fig. 3). Clearly, this frog leaping rule limits the local search space in each memetic evolution step. This limitation might not only slow down the convergence speed, but also cause premature convergence. In nature, because of imperfect perception, the worst frog cannot locate exactly the best frog's position, and because of inexact action, the worst frog cannot jump right to its target position. Considering these uncertainties, we argue that the worst frog's new position is not necessary restricted in the line connecting its current position and the best frog's position. Furthermore, the worst frog could jump over the best one. This idea leads to a new frog leaping rule that extends the local search space as illustrated in Fig. 4 (for 2-dimensional problems). The new frog leaping rule is expressed as:

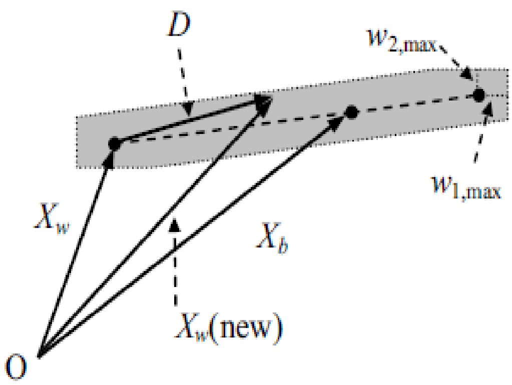

Figure. 4. The new frog leaping r

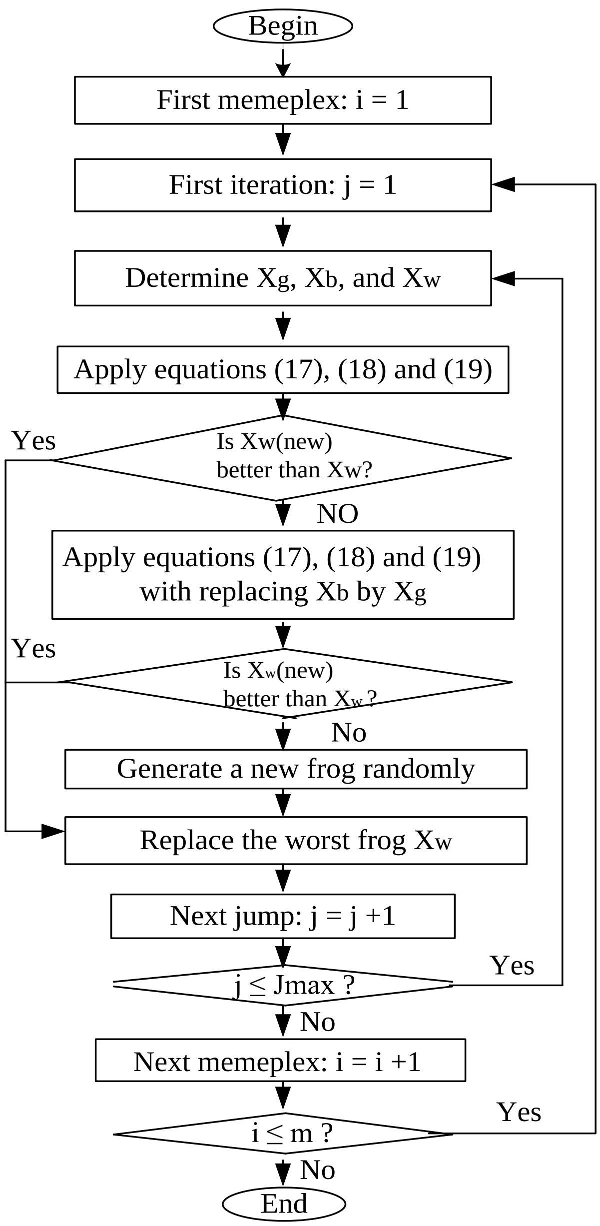

Figure. 5. Flow chart of the local search using the new frog leaping rule

$$D = r.c(X_b - X_w) + W\,, \tag{17}$$

$$W = [r_1 w_{1,max}\,, r_2 w_{2,max}\,, \ldots, r_S w_{S,max}]^T\,, \tag{18}$$

$$X_w(new) = \begin{cases} X_w + D & \text{if } |D| \le D_{max} \\ X_w + \dfrac{D}{\sqrt{D^T D}} D_{max} & \text{if } |D| > D_{max} \end{cases}, \tag{19}$$

where r is a random number between 0 and 1; c is a constant chosen in the range between 1and 2; r_i ($1 \le i \le S$) are random numbers between −1 and 1; $w_{i,max}$ ($1 \le i \le S$) are the maximum allowed perception and action uncertainties in the i^{th} dimension of the search space; and D_{max} is the maximum allowed distance of one jump. The flow chart of the local memetic evolution using the proposed frog leaping rule is illustrated in Fig. 5.

The new frog leaping rule extends the local search space in each memetic evolution step; as a result it might improve the algorithm in term of convergence rate and solution performance provided that the vector $W_{max}=[w_{1,max}, \ldots, w_{S,max}]^T$ is appropriately chosen. However, if $|W_{max}|$ is too large, the frog leaping rule will loss its directional characteristic, and the algorithm will becomes more or less random search. Therefore, choosing a proper maximum uncertainty vector is an issue to be considered for each particular optimization problem.

4.3.3 MSFL algorithm for optimizing DG location and capacity for reduce losses and voltage profile

The sequential steps are as follows:

1. Begin;
2. Generate random population of P solutions (frogs);
3. For each individual i ϵP: calculate fitness (i);
4. Sort the population P in descending order of their fitness;
5. Divide P into m memeplexes;
6. For each memeplex;
7. Determine the best and worst frogs;
8. Improve the worst frog position using Eqs. (17) , (18)and(19);
9. Repeat for a specific number of iterations;
10. End;
11. Combine the evolved memeplexes;
12. Sort the population P in descending order of their fitness;
13. Check if termination=true;
14. End;

5. RESULTS AND DISCUSSIONS OF STANDARD IEEE 70 BUS SYSTEM

The tested system is a 11-kV radial distribution system having two substations, four feeders, 70 nodes, and 69 branches as shown in Fig.6. The load data and branch data are given in Table1.Data for this system are given in the Appendix [19].

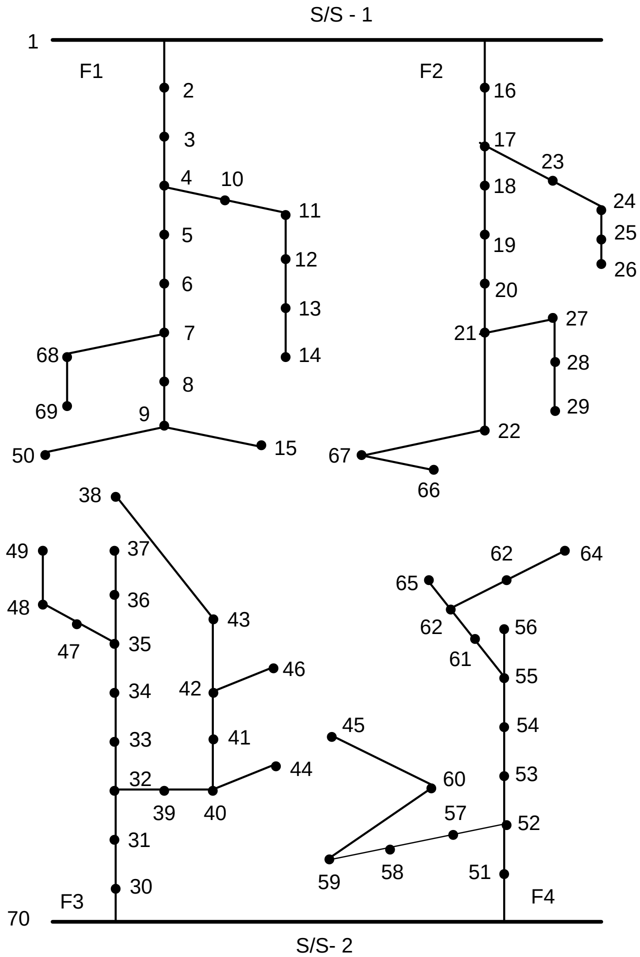

Figure 6. Standard IEEE 70 bus system

Table 1: Line and load data

Line no	From bus	To bus	R ^{ohm}	X ^{ohm}	PL^{KW}	QL^{KVAR}
1	1	2	1.097	1.074	100	90
2	2	3	1.463	1.423	60	40
3	3	4	0.731	0.716	150	130
4	4	5	0.366	0.358	75	50
5	5	6	1.828	1.790	15	9
6	6	7	1.097	1.074	18	14
7	7	8	0.731	0.716	13	10
8	8	9	0.731	0.716	16	11
9	4	10	1.080	0.734	20	10
10	10	11	1.620	1.101	16	9
11	11	12	1.080	0.734	50	40
12	12	13	1.350	0.917	75	60
13	13	14	0.810	0.550	25	15
14	14	15	1.944	1.321	40	25
15	7	68	1.080	0.734	80	50
16	68	69	1.620	1.101	40	30
17	1	16	1.097	1.074	60	30
18	16	17	0.366	0.358	40	25
19	17	18	1.463	1.432	15	9
20	18	19	0.914	0.895	13	7
21	19	20	0.804	0.787	30	20
22	20	21	1.133	1.110	90	50
23	21	22	0.475	0.465	50	30
24	17	23	2.214	1.505	60	40
25	23	24	1.620	1.110	70	65
26	24	25	1.080	0.734	75	65
27	25	26	0.540	0.367	75	60
28	26	27	0.540	0.367	80	55
29	27	28	1.080	0.734	85	70
30	28	29	1.080	0.734	95	70
31	70	30	0.366	0.358	70	50
32	30	31	0.731	0.716	60	40
33	31	32	0.731	0.716	13	8
34	32	33	0.804	0.787	16	9
35	33	34	1.170	1.145	50	30
36	34	35	0.768	0.752	40	28
37	35	36	0.731	0.716	60	40
38	36	37	1.097	1.074	40	30
39	37	38	1.463	1.432	30	25
40	32	39	1.080	0.734	75	45
41	39	40	0.540	0.367	60	35
42	40	41	1.080	0.734	65	50
43	41	42	1.836	1.248	60	30
44	42	43	1.296	0.881	18	10
45	40	44	1.188	0.807	16	10
46	44	45	0.540	0.367	80	50
47	42	46	1.080	0.734	60	40
48	35	47	0.540	0.367	80	65
49	47	48	1.080	0.734	65	40
50	48	49	1.080	0.734	75	60
51	49	50	1.080	0.734	70	45
52	70	51	0.366	0.358	60	40
53	51	52	1.463	1.432	20	11
54	52	53	1.463	1.432	40	30
55	53	54	0.914	0.895	36	24
56	54	55	0.914	0.895	30	20
57	55	56	1.097	1.074	43	30
58	52	57	0.270	0.183	80	50
59	57	58	0.270	0.183	85	60
60	58	59	0.810	0.550	65	45
61	59	60	1.296	0.881	25	10
62	55	62	1.118	0.807	10	5
63	61	62	1.118	0.807	90	60
64	62	63	0.810	0.550	125	110
65	63	64	1.620	1.101	30	20
66	64	65	1.080	0.734	130	120
67	65	66	0.540	0.367	75	60
68	66	67	1.080	0.734	25	15
69	9	50	0.908	0.726	-	-
70	9	38	0.381	0.244	-	-

5.1 Optimal allocation and sizing of distributed generation

Tables 2 shows the 70 bus radial systems optimal allocation and sizing of distributed generation by SFLA and proposed method (MSFLA) .For MSFLA and SFLA population size is 300. The maximum iteration for the MSFL algorithm is 5. The number of memplexes is 15. The number of frogs in memplex is 20. The Local iteration number in each

memeplexes is 5. The Global iteration number of algorithm is 5. The number of DG (DG is capable of supplying only real power) for Optimal allocation and sizing is 13 (thirteen). The maximum real power of DG is 50kw.

Table 2: Optimal DG allocation and sizing for DG

By MSFLA		By SFLA	
Bus no	**DG_{size}(kw)**	**Bus no**	**DG_{size}(kw)**
26	48.7225	54	42.7448
67	38.0563	14	41.5201
44	29.1158	68	15.0686
59	44.6827	6	45.6470
28	41.7856	45	35.9678
68	25.0144	16	45.5061
39	47.9189	18	49.1392
64	42.6504	27	43.1954
50	47.0747	35	43.4727
33	47.3473	66	27.9072
61	38.2382	25	46.9886
14	46.4518	40	39.8541
27	41.3904	43	44.4546

5.2 Results of power Loss Reduction and Improvement in Voltage Profile of the system

The reduction power loss is obvious after connecting thirteen DG as shown in Table 3 and Table 4. It indicates the reduction power losses with installation of DG for rating of 50 kw. The power loss for the base case without DG installation is calculated by load flow solutions and is found to be 205.0669 kw. For DG rating of 50 kw the values of power loss considerably reduces as indicated in Table 3 and Table 4.The percentage of power loss reduction is by means of (LLRI) and a reduction of 17.91 % is obtained with SFLA and a reduction of 18.35 % with MSFLA respectively.

Table 3. Power losses reduction results for a DG rating of 50 kw by SFLA

Method	DG rating of 50 kw		
	Power losses (kw)	LLRI	Reduction (%)
Base case	205.0669	-	-
SFLA	168.3249	0.8208	17.91

Table 4. power losses reduction results for a DG rating of 50 kw by MSFLA

Method	DG rating of 50 kw		
	Power losses (kw)	LLRI	Reduction (%)
Base case	205.0669	-	-
MSFLA	167.4329	0.8164	18.35

Table 5 and Table 6 indicates that for the SFLA and MSFLA methods considered, the values of the voltage profile of the system have improved considerably by connecting a DG of 50 kw capacities. The voltage profile of the base case was calculated to be 0.5157kv. When a DG rating of 50 kw were connected for case study by SFLA and MSFLA . The voltage profile of the system has improved which clearly indicates the need of a DG. The percentage of voltage profile improvement is by means of (VPII) and a improvement of 6.61 % is obtained with SFLA and a reduction of 7.09 % with MSFLA respectively.

Table 5. Voltage profile improvements for a DG rating of 50 kw by SFLA

Method	DG rating of 50 kw		
	VP(kv)	VPII	Improvement (%)
Base case	0.5157	-	-
SFLA	0.4816	0.9338	6.61

Table 6. Voltage profile improvements for a DG rating of 50 kw by MSFLA

Method	DG rating of 50 kw		
	VP(kv)	VPII	Improvement (%)
Base case	0.5157	-	-
MSFLA	0.4791	0.9290	7.09

Figure 7 and Figure 8 shows variation of improvement in voltage profile at bus 70 for a DG rating of 50 kw.

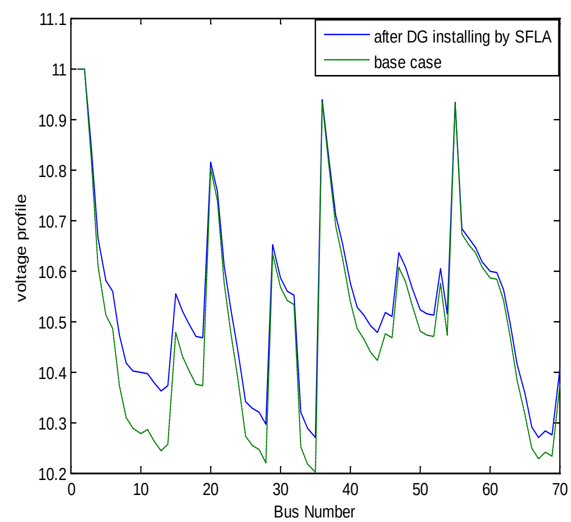

Figure 7.Voltage profile improvement results by SFLA

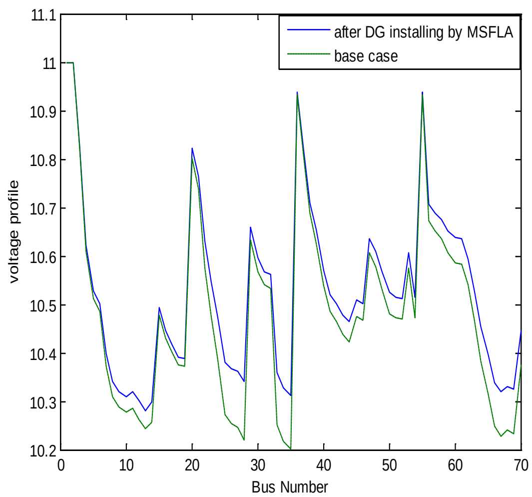

Figure 8. Voltage profile improvement results by MSFLA

Before Optimal placement and sizing of distributed generation, the minimum bus voltage is $V_{min}=V_{35}$=10.2001kv = 0.9272p.u. After Optimal placement and sizing of distributed generation by SFLA and MSFLA, the minimum bus voltage of the system has improved 10.2924kv=0.9356p.u. and 10.3106kv=0.9373 p.u respectively.

5.3 Comparison of objective function of SFLA and MSFLA

The problem is to determine allocation and size of the DGs which minimizes the distribution power losses and improve the voltage profile for a fixed number of DGs and specific total capacity of the DGs. Therefore, in this paper the objective function for the optimal placement and sizing of DG in distribution network problem is to minimize the real power losses and improve the voltage profile. The reduction objective function is evident after connecting thirteen DG by SFLA and proposed method (MSFLA) as shown in Table7. It indicates the reduction objective function with installation of DG for rating of 50 kw. The objective function for the base case without DG installation is calculated by load flow solutions and is found to be 102.7913kw.The percentage of objective function reduction of 12.76 % is obtained with SFLA and a reduction of 16.25% with MSFLA respectively.

Table 7. Comparison objective function results by SFLA and MSFLA

Method	After optimal allocation and sizing of DG	
	F_{total} (kw)	Reduction (%)
Base case	102.7913	-
SFLA	89.6709	12.76
MSFLA	86.0798	16.25

Table 7 shows the reduce in maximum objective function of the system after connecting DG at buses using the modified shuffled frog leaping algorithm.

6. CONCLUSION

The Distributed Generation (DG) in a distribution system offers several benefits such as relieved transmission and distribution congestion, voltage profile improvement, line loss reduction, improvement in system, and enhanced utility system reliability. The proposed work has presented an approach to quantity some of the benefits of DG namely, real power loss reduction and voltage profile improvement of system.

The results of the proposed method as applied to IEEE-70 bus system clearly show that DG can improve the voltage profile and reduce real power losses. Both ratings and locations of DG have to be considered together very carefully to capture the maximum benefits of DG. In this study shows The better capability of modified shuffled frog leaping algorithm (MSFLA) scale in shuffled frog leaping algorithm(SFLA) is to reduce the objective function by optimizing the DG allocation and capacity.

APPENDIX

Other data: current carrying capacity of all tie branches are 234.0 A. The current carrying capacity of branches 1 to 8, 17 to 23, 31 to 39, and 52 to 57 is 270 A. For branches 9 to 16, 24 to 30, 40 to 51, and 58 to 68, it is 208 A (see Table 1).

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